

# Image Splicing Detection involving Moment-based Feature Extraction and Classification using Artificial Neural Networks

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**Abstract** - In the modern age, the digital image has taken the place of the original analog photograph, and the forgery of digital images has become increasingly easy, and harder to detect. Image splicing is the process of making a composite picture by cutting and joining two or more photographs. An approach to efficient image splicing detection is proposed here. The spliced image often introduces a number of sharp transitions such as lines, edges and corners. Phase congruency is a sensitive measure of these sharp transitions and is hence proposed as a feature for splicing detection. Statistical moments of characteristic functions of wavelet sub-bands have been examined to detect the differences between the authentic images and spliced images. Image splicing detection can be treated as a two-class pattern recognition problem, which builds the model using moment features and some other parameters extracted from the given test image. Artificial neural network (ANN) is chosen as a classifier to train and test the given images.

**Keywords:** Image splicing, phase congruency, statistical moments, characteristic functions, wavelet decomposition, artificial neural network (ANN)

## I. INTRODUCTION

Image splicing, as its name implies, is a simple process of cropping and pasting regions from the same or different images to form another image without post-processing such as edge smoothing. Image splicing detection is hence urgently called for digital data forensics and information assurance. People need to know if a given image is spliced or not without any a priori knowledge[1,2].

In this paper, a novel approach to image splicing detection by exploiting the magnitude and phase information of a given test image is proposed. It is proposed to use the moments of wavelet characteristic function as one part of the image features to detect the spliced images.

The rest of this paper is organized as follows. Section 2 discusses the theory used for the detection of spliced images. In section 3, the methodology used for extraction of features is presented. Extraction of the features and subsequent training and classification using Neural Networks is discussed. Later in section 4, the discussion of the experimental results is presented. Finally conclusions are drawn in section 5.

## II. PROPOSED METHODOLOGY

The splicing detection can be considered as a two-class pattern recognition problem. The input images are categorized into two classes: spliced image and non-spliced (authentic) image.

### A. Moments of characteristic function

Image histogram has been widely used in image analysis. Any pmf ' $p_x$ ' may be expressed as a probability density function (pdf) ' $f_x$ ' by using the relation

$$f_x(x_0) = \sum_a p_x(a) \delta(x_0 - a) \quad (1)$$

Histogram of an image (or its wavelet subbands) and its CF is denoted by  $h(f_i)$  and  $H(f_k)$ , respectively. The  $n$ th moment of the CF is defined as follows.

$$M_n = \sum_{j=1}^{N/2} f_j^n |H(f_j)| / \sum_{j=1}^{N/2} |H(f_j)| \quad (2)$$

where  $H(f_j)$  is the CF component at frequency  $f_j$ ,  $N$  is the total number of points in the horizontal axis of the histogram.

### B. Prediction – Error Image

The prediction-error image is the difference between the test image and its predicted version. The prediction algorithm is given below.

$$\hat{x} = \begin{cases} \max(a, b) & c \leq \min(a, b) \\ \min(a, b) & c \geq \max(a, b) \\ a + b - c & \text{otherwise} \end{cases} \quad (3)$$

where  $a$ ,  $b$ ,  $c$  are the context of the pixel  $x$  under considerations,  $\hat{x}$  is the prediction value of  $x$ .

### C. 2-D Phase congruency

The image splicing leaves traces of image manipulation especially at locations where sharp image transition is introduced. Phase congruency (PC) was first defined by Morrone and Owens [9] in terms of the Fourier series expansion of a signal at some location  $x$  as

$$PC_1(x) = \max_{\bar{\phi}(x) \in [0, 2\pi]} \frac{\sum_n A_n \cos(\phi_n(x) - \bar{\phi}(x))}{\sum_n A_n} \quad (4)$$

where  $A_n$  is the amplitude of the  $n$ th Fourier component,  $\phi_n(x)$  is the local phase of the  $n$ th Fourier component at position  $x$ , and  $\bar{\phi}(x)$  is the amplitude weighted mean local phase angle at position  $x$ . Let the image be denoted by  $I(x, y)$ , the even-symmetric filter and odd-symmetric filter at scale  $n$  and orientation 'o' is denoted by  $M_{no}^e$  and  $M_{no}^o$ , respectively. The responses of each quadrature pair of filters are a vector:

$$[e_{no}(x, y), o_{no}(x, y)] = [I(x, y) * M_{no}^e, I(x, y) * M_{no}^o] \quad (5)$$

where  $*$  is the convolution operator. From Equation (5), the amplitude of this response is given by

$$A_{no}(x, y) = \sqrt{e_{no}^2(x, y) + o_{no}^2(x, y)} \quad (6)$$

and phase is given by

$$\phi_{no} = \text{atan}(e_{no}(x, y), o_{no}(x, y)) \quad (7)$$

The 2-D phase congruency is then calculated by

$$PC_2(x, y) = \frac{\sum_o \sum_n W_o(x, y) \lfloor A_{no}(x, y) \Delta\Phi_{no}(x, y) - T_o \rfloor}{\sum_o \sum_n A_{no}(x, y) + \epsilon} \quad (8)$$

Where  $\lfloor \cdot \rfloor$  denotes that the enclosed quantity is equal to itself if it is positive, and equal to zero otherwise;  $W_o(x, y)$  is a measure of significance of frequency spread;  $\epsilon$  is a small positive constant used to prevent division of zero;  $T_o$  is a quantity introduced to compensate image noise; and  $\Delta\Phi_{no}(x, y)$  is a sensitive phase deviation function defined as

$$\Delta\Phi_{no}(x, y) = \cos(\phi_{no}(x, y) - \bar{\phi}_o(x, y)) - \left| \sin(\phi_{no}(x, y) - \bar{\phi}_o(x, y)) \right| \quad (9)$$

### D. Feature extraction procedure

The first 78 dimensional features are collected from the test image  $I$  and its prediction-error image  $\hat{I}$ . For each wavelet subband, the first three moments are derived according to Equation (2), resulting in 39 dimensional features. Similarly, another 39 dimensional

features are extracted from prediction-error image. The additional 42 dimensional features are collected from three reconstructed images. To generate the reconstructed image  $I_{0i}$  ( $i = 1, 2, 3$ ) from the test image, Discrete Daubechies wavelet transform is applied on the test image. In other words,  $I_{01}$ ,  $I_{02}$ , and  $I_{03}$  are generated by erasure of approximation subband  $LL_1$ ,  $LL_2$  and  $LL_3$ , respectively.

### E. Neural network classifier

In this paper, an artificial neural network (ANN) [11], specifically, a perceptron, which is the simplest kind of feedforward neural network is used as a linear classifier.

The Perceptron is a binary classifier that maps its input  $x$  (a real-valued vector) to an output value  $f(x)$  (a single binary value) across the matrix.

$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{else} \end{cases} \quad (10)$$

where  $w$  is a vector of real-valued weights and  $w \cdot x$  is the dot product (which computes a weighted sum).  $b$  is the 'bias', a constant term that does not depend on any input value.

## III. IMPLEMENTATION

The image dataset is collected from DVMM, Columbia University. It consists of 933 authentic and 912 spliced image blocks in which all the image is of size 128x128. Examples of authentic and spliced image are shown in Figures 1 and 2 below respectively. More details about the image sets can be found in [4].

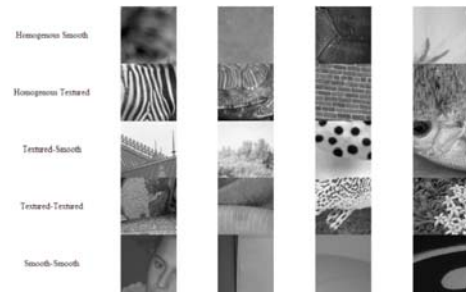


Figure 1. Examples of authentic images

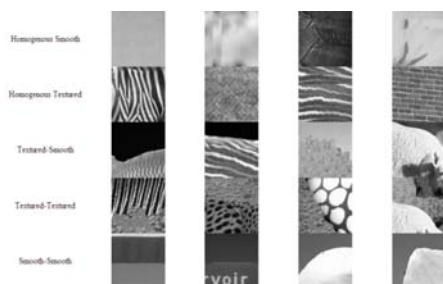


Figure 2. Examples of spliced images

TABLE 1 - Numbers of image blocks in different subcategories

Category	One Textured Background (T)	One Smooth Background (S)	Textured-Smooth Interface (TS)	Textured-Textured Interface (TT)	Smooth-Smooth Interface (SS)
Authentic (Au)	126	54	409	179	165
Spliced (Sp)	126	54	298	287	147

#### A. Extracting features from an image

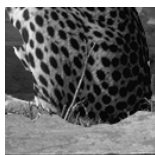


Figure 3. Original Image

##### A.1. Moments of Characteristic Function

Step 1 convert true color (RGB) image to a grayscale image

Step 2: Obtain the histogram of the grayscale image.

Step 3: Calculate the probability mass function and characteristic function..

##### A.2. Wavelet decomposition

Step 1: Perform single-level discrete 2-D wavelet transform on the image.

Step 2: Obtain the first three moments from all the approximation, vertical, horizontal and diagonal coefficient.

Step 3: After obtaining all the above coefficients, reconstruct the image is reconstructed using single-level inverse discrete 2-D wavelet transform.

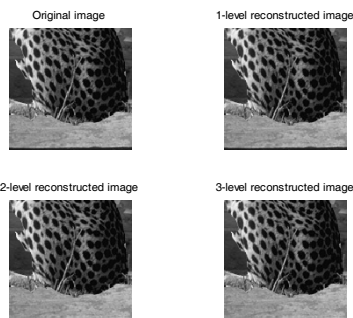


Figure 4. Three-level wavelet reconstruction of original image

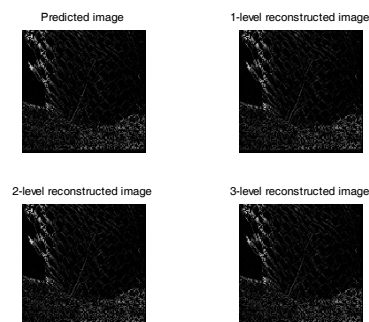


Figure 5. Three-level wavelet reconstruction of predicted image

#### A.3. Prediction –Error Image

Step1: Using the prediction algorithm as given in section 2, each pixel grayscale value in the original test image is predicted by using its neighboring pixels' grayscale values.

Step2: Obtain a prediction-error image by subtracting the predicted image from the test image.

Step 3: Perform 3-level wavelet decomposition of the predicted image.

Step 4: Calculate the first three moments from the coefficients of the of the prediction-error image.

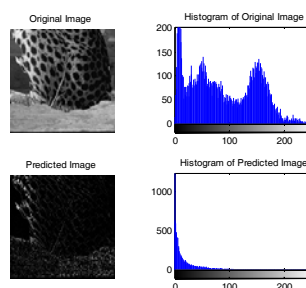


Figure 6. Comparison of histograms of original and predicted images

#### A.4. Phase Congruency

Step 1: Calculate phase congruency of the images.

Step 2: Extract seven image features from the measure of phase congruency – first three mean, variance and skewness.

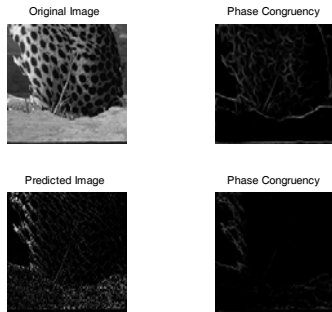


Figure 7. Extraction of phase congruency of original and predicted images

#### A.5. Edge Detection

Step 1: Extract the edges of the image.

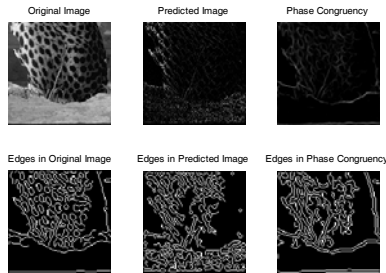


Figure 8. Extraction of edges of original, predicted and phase congruency images

#### A.6. Final Feature Extraction

Step 1: First 78 dimensional features are collected from the test image  $I$  and its prediction-error image  $\hat{I}$ . Step 2: 3-D Daubechies wavelet decomposition is performed on the test image.

Step 3: For each wavelet subband, the first three moments are derived according to Equation (2), resulting in 39 dimensional features.

Step 4: Similarly, another 39 dimensional features are extracted from prediction-error image.

Step 5: The additional 42 dimensional features are collected from three reconstructed images generated from the test image and three reconstructed images generated from the prediction-error image.

Step 6: From each reconstructed image  $I_{0i}$  ( $i = 1, 2, 3$ ), seven image features: first three moments are calculated according to Equation (2), and four statistics – mean,

variance, skewness and kurtosis – are computed based on 2-D array of phase congruency of the reconstructed image.

Step 7: The same procedure is conducted for each reconstructed image  $\hat{I}_{0i}$  ( $i=1, 2, 3$ ) from the prediction-error image to collect another group of seven features.

#### B. Forming of feature database

Step 1: Store all the 120 variables collected from each image as a row vector with 120 elements.

Step 2: Collect all 120 variables from all 1845 images (933 authentic + 912 spliced).

Step 3: Save the entire variable set as a 1845 x 120 matrix to facilitate easy computation later.

#### C. Image Classification

Step 1: A database of all parameters are collected from all the images

Step 2: Inputs are accepted from user:

Step 3: The user is asked to select any random image to be sent to the neural network

Step 4: The given image is classified into different subcategories

Step 5: The output is displayed.

#### D. Mode of Classification

- Classification of the images is done using 4 perceptrons.
- There are totally 1845 images in the dataset, with 120 different features being extracted from each.
- Hence each perceptron receives 120 inputs, from 1845 images.

## IV. RESULTS AND DISCUSSIONS

#### Detection Rates

The average detection rate of the experiments is shown in Table 2, where TP (true positive) represents the detection rate of spliced images, TN (true negative) represents the detection rate of authentic images, and accuracy is the average detection rate.

TABLE 2 - Detection rates using a Perceptron-based classifier

Training Size	9/10		
	TP	TN	Accuracy
Perceptron	0.9605	0.9475	0.9540
Training Size	5/6		
	TP	TN	Accuracy
Perceptron	0.9178	0.9164	0.9171
Training Size	$\frac{1}{2}$		
	TP	TN	Accuracy
Perceptron	0.7785	0.7513	0.7649
Training Size	$\frac{1}{3}$		
	TP	TN	Accuracy
Perceptron	0.6590	0.6624	0.6607

## V. CONCLUSION

In this paper, a new modified splicing detection scheme is proposed. To detect the spliced images, the distinguishing image features are extracted by exploiting both magnitude and phase information of a given image. The first part of image features is the statistical moments of characteristic functions of a test image, its prediction-error image, and their wavelet subbands. The methodology implemented in this paper reduces the computation time and maintains good accuracy.

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